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Abstract

Landscape and temporal patterns of temperature were observed for local (13 station) and regional (35 station) networks in the southern Appalachian Mountains of North America. Temperatures decreased with altitude at mean rates of 7°C/km (maximum temperature) and 3°C/km (minimum temperature). Daily lapse rates depended on the method and stations used in the calculations. Average daily temperature ranges decreased as elevation increased, from 14°C at 700 m to 7°C at 1440 m, and daily temperature ranges were typically higher in spring and fall at any given station. Daily maximum temperatures above the forest canopy averaged 1.4°C higher at a south-facing station relative to a comparable northwest-facing station, and above-canopy daily minimum temperatures were depressed at a valley-bottom station. Regional regression models provided a more accurate estimates of station temperature than either kriging or local lapse models when tested using 35 National Climatic Data Center (NCDC) stations in the southern Appalachians. Data-splitting tests yielded mean absolute errors (MAE) from 1.39 to 2.30°C for predictions of daily temperatures. Ten-year biases for an independent data set collected at four stations in the Coweeta Basin ranged from −2.87 to 2.91°C for daily temperatures, with regional regression performing best, on average. However tests against another independent data set indicate regional regression and local lapse models were not significantly different, with mean biases averaged from −2.78 to 2.91°C for daily predicted temperatures.

1. Introduction

The rates of most biotic processes, including phenologies, growth, carbon fixation, and respiration are directly affected by temperature (Cantlon, 1953; Lechowicz, 1984; Aber and Melillo, 1991; Waring and Schlesinger, 1985). Organisms, species, and communities respond to changing temperatures on diurnal, seasonal, annual, and longer time spans. Temperature affects plant moisture requirements and plant water relations (Larcher, 1975; Kramer, 1983), and interacts with terrain, soils, and insolation, and these interactions cumulatively impact tree growth, species composition, detrital production, and susceptibility to disturbance (Turner and Gardner, 1991). Two overriding themes of forest research over the last few decades have been a process-based understanding of the effects of environmental variables such as temperature on forest ecosystems, and the extension of

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this understanding to landscape scales. These themes have driven the development of models that predict important environmental parameters, such as temperature, at landscape scales (Pielke and Mehring, 1977; Running et al., 1987). Despite this, there are relatively few empirical evaluations of landscape-scale temperature prediction techniques, and there have been particularly few tests of methods that predict temperature at both high spatial resolution and temporal frequency. We require better methods for predicting the landscape temperature if we are to develop landscape-scale, process-based models of mass and energy cycles in forest ecosystems.

A number of landscape temperature prediction methods have been developed for the various ecosystems and conditions (e.g., Leffler, 1981; Boyer, 1984; Russo et al., 1993; Régnière and Bolstad, 1994; Régnière, 1996; Bolstad et al., 1997). The vertical lapse method is perhaps the most common, particularly in areas with mountainous or complex terrain. This method adjusts for the commonly observed decrease in temperature with an increase in elevation (Barry, 1992). These temperature/elevation relationships are applied to a known time series of temperatures measured at a base station, adjusting for the elevation difference between the base and target location. Lapse-rates have been incorporated in many models, and these rates may be allowed to vary with season, month or atmospheric conditions (Running et al., 1987; Aber and Federer, 1992). Lapse models are most often applied to monthly averages or daily extremes, and if finer temporal resolution is required, hourly or finer data are often interpolated using trigonometric or mixed trigonometric/exponential functions (Parton and Logan, 1981; Hungerford et al., 1989).

Lapse models are attractive because they are simple to understand and apply and require fewer data than many other methods. However, the quality of lapse predictions depends substantially on the stations chosen and the details of the method used. Although all regional interpolation or prediction methods are influenced by the local temperature anomalies such as cold air drainage or katabatic winds (McCutchan and Fox, 1986; Barry, 1992), lapse models may be particularly susceptible, causing anomalous temperatures at a single base station to be extrapolated across large areas. In addition, lapse (and most other) methods by themselves do not incorporate other terrain-related temperature effects, such as those due to the differential solar insolation (south vs. north slopes), perhaps due to the lack of a strong theoretical foundation and few empirical data on which to base such adjustments.

Regional regression is a second common spatial interpolation technique. These methods employ a network of temperature measurement stations and typically fit polynomial equations. The equations predict annual, monthly, or daily mean or extreme temperatures as functions of elevation and horizontal coordinates (Russo et al., 1993). Regional regressions reduce susceptibility to the anomalous behavior caused by a single, biased base station. However, regression coefficients depend on the set of stations used, and regression models may not be possible where temperature measurement stations are sparse, as in remote mountainous or unpopulated regions.

Both lapse and regional regression relationships have been incorporated in models which predict forest processes or events at landscape-scales (Russo et al., 1993; Régnière and Bolstad, 1994; Schaub et al., 1995; Régnière, 1996; Bolstad et al., 1997). These models use weather data from single or multiple sources to predict a spatial field of temperature-dependent phenomena, e.g., forest pest egg hatch, development, or emergence. These modeling systems have a number of uses, including population simulation, analyses, and event forecasting. Forecasting applications generally incorporate both the relevant recent temperature record and simulated future temperature to predict the specific target events, and the application and utility of these systems have been demonstrated (Régnière and Bolstad, 1994; Régnière, 1996).

Geostatistical techniques are relatively new, and have also been applied to predict environmental variables at landscape scales. Kriging and other geostatistical techniques incorporate spatial autocorrelation, and statistically optimize the weights when combining regional stations (Isaaks and Srivatstava, 1989). This process requires an assumption regarding the shape of the spatial covariance or correlation functions. Parameters of the autocorrelation function are estimated using the spatially-referenced measurement set, and predictions at unmeasured points made from the spatial covariance functions and measured data. These methods may be particularly appropriate for temperature predictions in regions with little topographic relief, and where there may be significant local temperature effects, such as near large water bodies. In addition, related techniques such as co-kriging may be used when there are appropriate spatial covariates. However, as with regional regression models, kriging and related techniques are not useful where temperature measurement stations are sparse, and even under the most dense sampling, station densities may not be high enough to reflect the short-distance local terrain effects. While geostatistical methods show promise, they have not been well tested, particularly for predicting daily temperature.

There have been relatively few studies comparing the relative performance of current (lapse and regional regression) and geostatistical techniques for predicting the daily maximum and minimum temperature. The bias and precision of these regional temperature prediction models must be determined if the models are to be effectively applied for predicting the temperature-dependent phenomena. Errors may be derived from several sources, e.g., temperatures are generally higher on south-facing slopes in an amount that varies by time of year, slope position, and canopy characteristics, and cold air drainage may depress minima and valley bottom locations (Tajchman and Minton, 1986; Barry, 1992). There were four objectives in this study:

1. Compare regional lapse, regional regression, and kriging temperature prediction methods in the mountainous terrain of eastern North America,
2. more completely characterize the temperature prediction errors when using regional regression,
3. compare the spatial temperature predictions based on local lapse and regional regression models to field-measured air temperatures, and,
4. evaluate local terrain effects on local lapse and regression predictions.

2. Methods

Analyses were based on three meteorological data sets. The first was a regional set (hereafter referred to as the 'regional' data), comprised of daily maximum and minimum temperatures distributed by the National Climatic Data Center (Earth Info, 1993, Boulder, CO). Daily extremes were analyzed for the 35 stations found from 35° to 36°30′N latitude and 82°15′ to 84°15′W longitude (Table 1). Analyses were restricted to stations with 90% or more data for years 1986 through 1995. Station elevation ranged from 239 to 1967 m. Temperatures were measured using a variety of instruments, most commonly with glass thermometers, but also with thermistors or thermocouples. Station horizontal location was reported to the nearest minute of arc, and elevation to the nearest meter. Data quality and errors were identified (Reek et al., 1992), and adjusted as appropriate. A total of 240 937 daily maximum and minimum observations were available.

Table 1
Regional weather station characteristics

ID	Station Name	Elevation	Latitude	Longitude
184	Andrews	530	35°12′N	83°50′W
300	Asheville AP	648	35°26′N	82°33′W
301	Asheville	689	35°36′N	82°32′W
724	Bent Creek	639	35°30′N	82°36′W
843	Black Mountain	694	35°37′N	82°21′W
1055	Brevard	652	35°14′N	82°44′W
1094	Bristol	463	36°29′N	82°24′W
1441	Canton	806	35°31′N	82°51′W
1564	Cataloochee	794	35°37′N	83°06′W
2102	Coweeta Exp Stn	682	35°04′N	83°26′W
2200	Cullowhee	663	35°19′N	83°11′W
2934	Erwin	521	36°08′N	82°26′W
3101	Fletcher 4E	654	35°26′N	82°26′W
3106	Fletcher 3W	627	35°26′N	82°34′W
3228	Franklin	630	35°11′N	83°23′W
3679	Greeneville	400	36°06′N	82°51′W
3976	Hendersonville	684	35°20′N	82°27′W
4055	Highlands	1163	35°03′N	83°11′W
4260	Hot Springs	403	35°54′N	82°49′W
4613	Jefferson City	354	36°09′N	83°27′W
4950	Knoxville	266	35°49′N	83°59′W
5158	Lenoir City	239	35°48′N	84°15′W
5356	Marshall	606	35°48′N	82°40′W
5923	Mt. Mitchell	1891	35°46′N	82°16′W
6328	Mt. Leconte	1967	35°39′N	83°26′W
6271	Morristown	412	36°12′N	83°17′W
6341	Oconaluftee	618	35°31′N	83°18′W
6534	Newport	315	35°59′N	83°12′W
6750	Oakridge	272	36°01′N	84°14′W
6805	Pisgah Forest	639	35°16′N	82°42′W
7884	Rogersville	412	36°25′N	82°59′W
8179	Sevierville	281	35°52′N	83°33′W
8448	Swannanoa	1309	35°34′N	82°23′W
8868	Tazewell	415	36°28′N	83°33′W
9123	Waterville	436	35°46′N	83°06′W

Table 2
Characteristics for meteorological stations located in the Coweeta Basin

Station number and type	Record period	Elevation (m)	Terrain position	Aspect	Slope (%)
CS01 Basin	1/1/1986 12/31/1995	694	Valley bottom	Flat	0
CS17 Basin	1/1/1986 12/31/1995	874	Sideslope	N30°W	32
CS21 Basin	1/1/1986 12/31/1995	848	Sideslope	S2°E	21
CS28 Basin	1/1/1986 12/31/1995	1202	Sideslope	N90°E	43
CS77 Basin	5/1/1992 12/31/1995	1439	Ridge	N2°W	18
L2 Canopy	1 May–15 October 1992 and 1993	745	Cove–Sideslope	S42°E	42
H2 Canopy	1 May–15 October 1992 and 1993	830	Sideslope	S8°E	22
L27 Canopy	1 May–15 October 1992 and 1993	1086	Cove	N55°E	15
H27 Canopy	1 May–15 October 1992 and 1993	1411	Ridge shoulder	N22°E	23

The second data set is comprised of a five-station network located within the research watershed of the Coweeta Hydrologic Lab located at 35°03′N latitude, 83°27′W longitude, near Otto, NC (hereafter referred to as the 'basin' data set). Stations represent a range of terrain and elevation conditions, including low elevation mountain valley (Station CS01), low elevation north facing (Station CS17) and south facing slopes (Station CS21), mid elevation east slope (Station CS28) and a high elevation ridgetop (Station CS77) locations. This network, established and maintained since the early 1930s by the US Forest Service, records hourly meteorological data (Table 2). Stations consist of standard weather shelters located in approximately 0.2 ha clearings. Herbaceous or short woody vegetation (<0.2 m) covers the clearings, which are surrounded by mature, closed-canopy forests. Temperatures are measured and recorded using thermistors prior to 1992, and Copper–Constantan thermocouples thereafter. Temperatures were recorded to the nearest 0.1°, with calibrated accuracy greater then 0.5°C and typically accurate to the nearest 0.2°C. Temperature readings were checked monthly against high accuracy, mercury-filled thermometers. Station locations were determined with global positioning system (GPS) receivers, differentially corrected to the nearest 5 m. Data for the 1986 through 1995 period of record were extracted for these analyses. All the station data were greater than 99% complete for this interval, with the exception of Station CS77, established in early 1992. Data for Station CS77 were greater than 99% complete for the period of record.

The third data set consists of hourly temperature measurements for the 1992 growing season, taken atop canopy towers (the 'canopy' data set). Four towers were erected to extend above the canopy at low elevation toeslope (L2), low sideslope (H2), mid elevation cove (L27), and high elevation ridgetop (H27) sites. Temperatures were measured in standard weather shelters mounted at tower heights from 18 to 24 m, approximately 1 m above the local forest canopy in all the cases. Temperatures were recorded each minute and averaged hourly using special limits of error Copper–Constantan thermocouples (Omega Engineering). Data were collected from Julian day 121 through 267, 1992. Thermocouple readings were calibrated against 0.1°C accurate glass thermometers, traceable to national standards.

Data sets were combined by date and as appropriate by hour. Maximum and minimum daily temperatures were calculated for all the three sets. Monthly average, standard error, and variance of the daily maxima and minima were calculated. Two-station local lapse rates were calculated from the basin data set, comparing (a) valley bottom (Station CS01) to mid elevation (Station CS28), (b) valley bottom (Station CS01) to high elevation (Station CS77), and (c) average of the low sideslope Stations (CS17 and CS21) to mid elevation sideslope (Station CS28), and the average of the low sideslope Stations (CS17 and CS21) to high elevation Station (CS77). Regional lapse rates were calculated from the regional data set via first-degree regressions between temperature maxima/minima and station elevation.

Three different regional temperature prediction model forms were applied to the regional data set. Daily models were fit for regional lapse rate, regional regression, and kriging models to predict the daily maxima and minima and seasonal mean temperatures. Regional lapse rate methods predicted temperature for a regional station based on:

$$T_{w,i} = T_0 + \Delta Z \cdot \theta_{p,i} \tag{1}$$

where $T_{w,i}$ is the predicted temperature (maximum or minimum) for the withheld station, T_0 the temperature measured at the nearest remaining regional station, ΔZ is the elevation difference between the nearest station and predicted regional station, and $\theta_{p,i}$ the regional lapse rate for variable p (maximum and minimum temperature), and day i. Regional lapse rates were calculated using simple linear temperature/elevation regressions:

$$T_i = \theta_0 + \theta_{p,i} \cdot Z \tag{2}$$

where T_i is the daily temperature for the retained stations and the remaining parameters are as described above.

The regional regression predictions were based on a second-degree polynomial:

$$T_i = \beta_0 + \beta_1 \cdot X + \beta_2 \cdot X^2 + \beta_3 \cdot Y + \beta_4 \cdot Y^2 + \beta_5 \cdot XY + \beta_6 \cdot Z \tag{3}$$

where T_i's are the predicted daily extreme temperature, β's are the fit regression coefficients, and X, Y, and Z are easting, northing, and elevation, respectively.

Autoregressive moving average (ARIMA) models were fit to daily deviations of regional regression coefficients from 10-year normal values. Previous work has documented autocorrelation among daily minima and maxima temperature time series, and among deviations of daily extreme temperatures from long-term normals (Régnière and Bolstad, 1994). ARIMA models with up to five-day lags were fit to maximum and minimum temperature coefficients β_0 through β_6 in regional regression models (Box and Jenkins, 1976), and significance determined by Durbin–Watson tests.

Kriging models were based on:

$$T_i = \sum_{i=1}^{n} \lambda_j \cdot T_j \tag{4}$$

where T_i is the predicted temperature, λ_j are weights from the fit variogram model (Cressie, 1985), and T_js were the temperatures measured at each of the station. Observed variograms were fit according to:

$$\gamma^*(h) = \frac{1}{2N(h)} \sum_{i=1}^{N(h)} -z(x_i + h) - z(x_i)^2 \tag{5}$$

where γ^* is the semivariance, h is the lag distance, and T_i and T_j measured temperatures.

Preliminary analyses indicated little difference among semivariogram model forms, thus spherical variogram models were typically used although exponential and Gaussian models occasionally provided better fits. Kriging semivariance functions were fit iteratively, manually selecting the best indicative goodness of fit (Pannatier, 1993).

Iterative data splitting was used in all the regional temperature prediction models to assess the relative predictor bias and precision. Errors were determined by successively withholding each station in the regional data set, estimating required parameters for the various models, and calculating the difference between the predicted and observed daily extremes for each withheld point. By iterating through all stations, we obtained measures of the relative performance of each method. Manual fits placed an upper limit on the number of kriging analyses which could be performed, in that 35 kriging models, one for each withheld station, were required for each comparison, and the process could not be automated. Thus, ten days were randomly selected from the regional data set. Comparisons of daily predictions based on regional model were restricted to these days. Bias, MAE, and standard deviation were computed for each of the three regional prediction methods.

Based on the results from the above studies, our next set of analyses combined the regional, basin, and canopy data sets to estimate errors in predicted temperatures when using the regional regression and local lapse-rate models. Our basic goal was to determine the typical and maximum error when predicting daily maximum and minimum temperatures using these two methods. Daily regional regression models (Eq. (3)) for maximum and minimum temperature were fit for each day in 1992 using the regional data set. Maximum and minimum temperatures were predicted for each basin and canopy station, using these regional models and regional data set. Prediction errors were then computed as predicted minus site-measured maximum and minimum temperatures for withheld sampling locations in the Coweeta basin. Summary statistics were determined, including the average error (bias), mean absolute error, and standard deviation. We calculated prediction errors for the lapse rate method in a similar fashion. Basin and canopy data sets were used to estimate the prediction errors when using local lapse-rate models:

$$T_i = T_b + \Delta Z \cdot \theta_{\mathrm{d.b}} \tag{6}$$

where T_i is the predicted daily maximum or minimum temperature, T_b is the corresponding daily maximum or minimum base station temperature, ΔZ is the elevation difference between the base station and sample station, and $\theta_{\mathrm{d.b}}$ is the maximum or minimum daily temperature local lapse rate between base (b) and upper elevation (d) basin or canopy stations:

$$\theta_{\mathrm{d.b}} = \frac{T_{\mathrm{d}} - T_{\mathrm{b}}}{Z_{\mathrm{d}} - Z_{\mathrm{b}}} \tag{7}$$

Daily local lapse rates were calculated from the low-sideslope (CS17 and CS21) to the high sidelslope (CS28) and ridge (CS77) sites for JD 121 through Julian day 279, periods approximately spanning the 1992 growing season. We note that these 'local' lapse rate Eqs. (6) and (7) differ from the 'regional' lapse rates Eqs. (1) and (2), in that the local models use station pairs with a large elevation difference, and calculate daily lapse rates by the temperature difference observed at these stations. The regional lapse models (Eqs. (1) and (2)) fit a linear equation to a daily set of observations, regressing temperature at each station against elevation. The slope of the regression, estimated for each day in the record, is the regional lapse rate. Daily-determined lapse rates for Eqs. (6) and (7) were applied to predict the maximum and minimum temperatures for each of the canopy stations, using CS17 and CS21 as base stations, applying canopy site/base station elevation differences with the calculated lapse rates to estimate temperature. Predicted minus observed temperatures were determined for each canopy site, and summary statistics calculated.

We emphasize that the predicted minus observed prediction errors were based on the sets of stations not used in fitting the daily lapse and the regional regression models, and are in that sense independent from the models. However the prediction errors for each station form time series which may be temporally autocorrelated and cross-correlated between stations. Poor or good prediction may be clustered in time, or model performance may vary regionally, so that the basin and canopy stations may tend to have high and low errors in concert. Such correlations would confound significance tests. Autoregressive models with up to five-day lags were fit to the prediction error time series for the canopy and basin stations. Model parameters were estimated using a maximum likelihood algorithm (SAS autoreg and pdlreg, SAS Institute, 1988), and appropriate weighted variances and significance tests performed.

The acceptable limit of temperature prediction errors depends on the application. For example, models which depend on monthly averages require only that daily prediction models have low bias; processes with a more rapid, nonlinear response to temperature, such as respiration, will be affected by both bias and imprecision in daily temperature predictions. Our final set of analyses used the 'best' temperature prediction method, regional regression, for predicting the two temperature-dependent phenomena. Eq. (3) models were fit using the regional temperature data, and resultant models used to predict daily maximum and minimum temperatures at each of the five stations in the basin data set. Daily temperatures were predicted for the period 1986–1995. Bud burst for most species begins at the accumulation of approximately 175 degree-days, 7.5°C base, and leaf expansion is complete at 350 degree-days. Spring bud burst and full-leaf expansion dates were predicted for each basin station in each year, based on the observed and predicted degree-days. Growing season leaf respiration for each of the basin stations was also predicted, using observed canopy station data and temperatures predicted from the regional regression (Eq. (3)) models.

These temperature data were combined with local leaf temperature/respiration functions (Vose and Bolstad, 1998) and Coweeta average leaf biomass data to predict the growing-season aggregate canopy respiration.

3. Results and discussion

3.1. Station temperatures

As expected, temperatures typically decreased as elevation increased (Fig. 1). This trend occurred for most temperature variables in both the canopy and basin data sets. Daily maximum temperatures were warmest at the lower elevations (CS01, CS21, and CS17), and decreased for the successively higher elevation stations (CS28 and CS77). Differences were

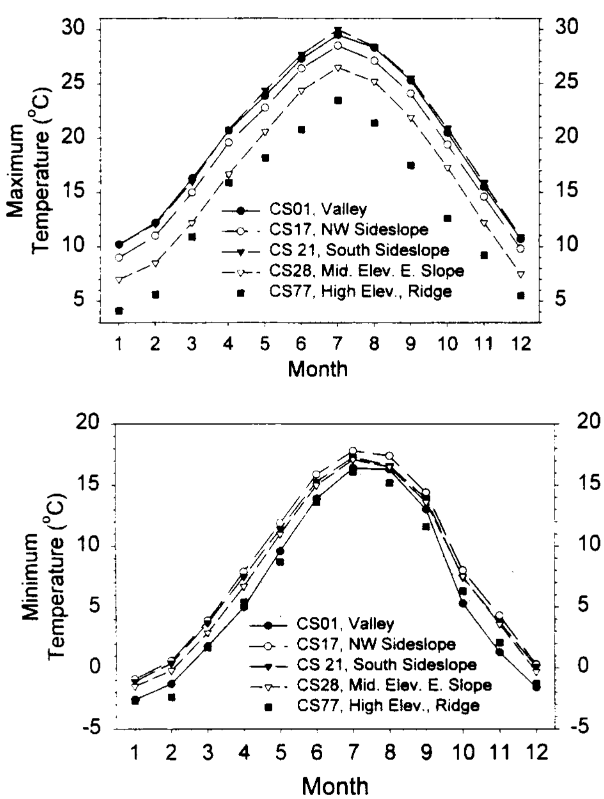

Fig. 1. (a) (top) Daily maximum and (b) (bottom) minimum air temperatures, averaged monthly for the period 1986–1995 for stations at various terrain positions within the Coweeta Basin, NC.

generally consistent across months (Fig. 1(a)). Daily minimum temperatures were more similar among stations than daily maxima, and station rank order for minima varied more by the time of year. Mean daily minimum temperatures observed at the valley bottom station, CS01, were generally lower than the mean daily minima at other stations, except the high elevation ridge station (Fig. 1(b)). Mean temperatures for station CS01 were 0.4 to 0.9°C lower than nearby sideslope stations CS21 and CS17, and mean daily minimum temperatures averaged 1.8°C lower at station CS01. Mean daily minima at station CS01 were lower than those observed at the higher elevation stations CS28 and CS77 when averaged over the entire year and growing season (May through mid-October), even though CS01 was at an elevation 500 to 700 m lower. Cold air drainage, predominantly at night-time, has been observed to cause these depressed minima in valleys, particularly when the local topography leads to the collection and pooling of downslope airflow (Bergen, 1969; Kaufmann, 1984; Toritani, 1990; Barry, 1992). Depressed minimum temperatures were more common during nights with low windspeed (<15 km/h), and were observed for all months of the year, but were more frequent during the leaf-off period, late October through mid-April.

Temperatures observed at low-elevation sideslope stations indicate a small but consistent exposure-related maximum temperature increase. Daily maximum temperatures at CS21 (southern exposure) averaged 1.4°C higher than CS17 (northwestern exposure), a station at a similar elevation and terrain shape. This exposure-related increase was consistent across all the months of the year for the basin data set (Fig. 1(a)). There was little effect of exposure on the mean above-canopy daily minimum temperature, and average temperatures at station CS21 were 0.2°C lower than the comparable station CS17.

There were small but significant effects of exposure on daily above-canopy minimum and mean temperatures. These observations are quite comparable with those of Cantlon (1953). Using the north–south exposure scale, of Régnière (1996):

$$\Lambda = \text{slope} * \{\cos^2(\text{latitude})^* \phi + \sin^2(\text{latitude}) Cos(\text{aspect} - 15)\} \quad (8)$$

where latitude is in degrees North, measured clockwise and slope is in degrees, $\phi = -1$ for aspects from

135° to 255°, and ϕ=1 otherwise. We calculated that site CS17 has a 16° northern exposure Λ and site CS21 an 11.7° southern exposure. Thus, our observations represent an average minimum temperature increase of 0.5°C per 10° southern exposure, a value quite similar to the observations made in the other eastern North American and European forest canopies (see Régnière, 1996). These exposure-related maximum temperature differentials are small relative to observations made by several others (Pielke and Mehring, 1977; Kaufmann, 1984; Barry, 1992). Several reasons may explain these differences. Frequent cloud cover accompanies frequent, well distributed rainfall at the Coweeta Basin. Insolation is attenuated by the atmospheric moisture and cloud cover, and hence reduces the potential differences in temperature due to differences in site exposure. In addition, soil moisture is typically high for most of the growing season and all of the dormant season. Much of the increased insolation on southern-exposure sites may be converted to latent heat, reducing exposure-related differences that have been theoretically determined or observed in drier climates.

Daily temperature range generally decreased as station elevation increased, and was also influenced by time of the year, local terrain shape, and station exposure (Fig. 2). Temperature range was the highest for the low elevation valley bottom station (CS01), particularly so during spring and fall. CS21 had the next highest mean daily temperature ranges, due to the elevated maxima at this south-facing station. Next

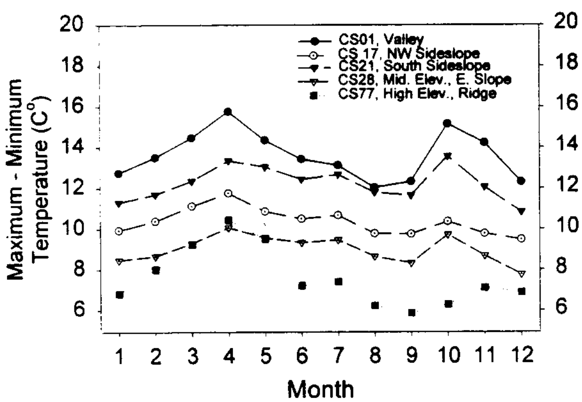

Fig. 2. Daily air temperature range, monthly averages for the period 1986–1995 for stations at various terrain positions within the Coweeta Basin, NC.

lowest temperature ranges were observed at the northeast sidelope station (CS17), and decreased successively for higher elevation stations. Decreasing daily temperature range with increasing temperature has been observed under a number of conditions and in a number of continents (Lauscher, 1966; Linacre, 1982). The ranges we observed were generally similar to those reported elsewhere in North America, but the daily temperature ranges were lower at our upper elevations than those reported in western North America, and more similar to those reported for the European mountains. Lauscher (1966) suggested that these continental differences may be due to the higher atmospheric moisture in Europe, conditions also more typical of eastern than western North America.

3.2. Local lapse rates

Daily lapse rates are not constant, and depended on time of the year and stations used in the calculations (Fig. 3). Maximum-temperature lapse rates varied from 4° to 10°C per 1000 m and were significantly higher in the spring than other months, (p=0.01) at least when based on station pairs in the Coweeta Basin data set. Maximum temperature lapse rates peaked in the summer when using the regional data set and were lowest in the winter. Daily maximum temperature lapse rates based on the sideslope-to-ridge station averaged 2°C higher than lapse rates based on valley bottom-to-ridge comparisons (CS01 to CS77), a difference that was consistent and statistically significant for all the months (Fig. 3(a)). These higher lapse rates were due to the noted lower minima observed at the valley bottom station. Daily maximum temperature lapse rates calculated from the regional data were consistently lower than the basin sideslope-to-ridge rates, and higher, the same as, or lower than basin valley-to-ridge lapse rates. Lapse rates depend on atmospheric moisture, temperature, and pressure (Rosenberg et al., 1983). Our observed lapse rates for the maximum temperature are typically below dry adiabatic lapse rate of 10°C/km elevation, not unexpected in this moist region. However dry adiabatic lapse rates have been used in models applied to this region, and our results indicated they should not be. Coweeta station measurements indicate that the maximum temperature lapse rates are highest just prior to the onset of meteorological spring (Schwartz, 1992),

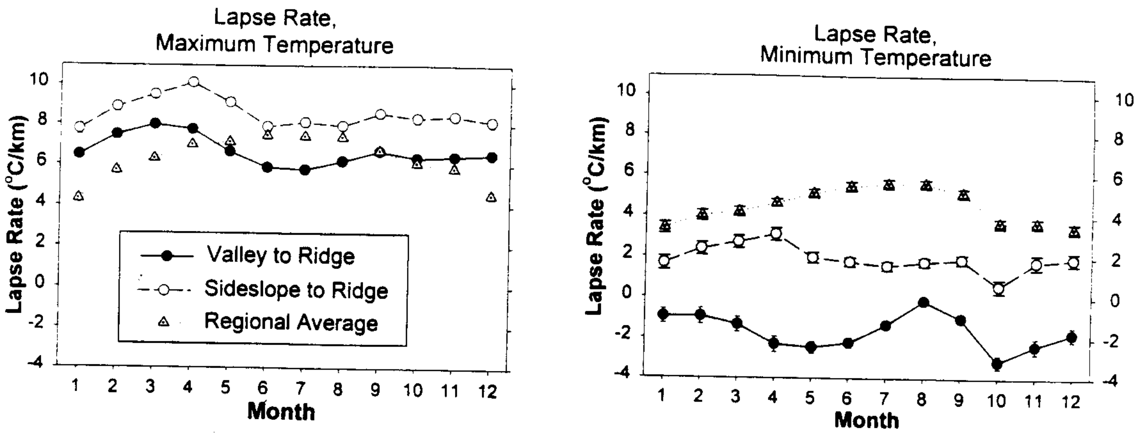

Fig. 3. (a) (top) Daily maximum and (b) (bottom), minimum temperature lapse rates calculated from local and regional regression analyses.

when temperatures are warming but prior to increased boundary layer thickness and increased atmospheric water vapor concentration.

Monthly averages of the mean daily minimum-temperature lapse rates ranged from −3.8 to 5.8°C, and varied by time of the year and stations used in the calculation (Fig. 3(b)). Minimum-temperature lapse rates based on the regional data set were always higher than lapse rates based on station pairs in the Coweeta Basin, a difference which was consistent across all months (Fig. 3(b)). Lapse rates including station CS01 were negative for all months of the year, reflecting the depressed minimum temperatures for that valley bottom station. As noted above, we attribute this to the cold air drainage, as these minimum-temperature inverted lapse rates were larger and more consistent on nights with lower night-time windspeed (t-test of means, windspeed above and below 10 km/h, $p<0.05$). Minimum temperature lapse rates based on the basin sideslope-to-ridge stations (CS17 and CS21 to CS28) varied from 1 to 3°C/1000 m, significantly different from those observed when using valley bottom station CS01 in the lapse rate calculations (Fig. 3(b)). Minimum temperature lapse rates based on the basin stations were also more variable during winter months and less variable during summer months, and were consistently more variable than the corresponding maximum temperature lapse rates (Fig. 3(a) and (b)). Minimum temperature lapse rates based on the non-valley stations are close to the expected wet adiabatic lapse rates (3 to 4°C/km) for most of the year. We note that there were large and significant differences between regional and basin-derived estimates.

Mean temperature lapse rates for our sites are similar to those reported by Leffler (1981) for Appalachian summits. Mean lapse rates observed for the basin and canopy data sets are slightly higher in summer and slightly lower in winter (≈0.5°C/km in each instance) in our study. There is a good general agreement, particularly given that Leffler used a small set of only mountaintop stations, a much larger geographic range, and a different period of record. Our maximum temperature lapse rates based on the sideslope-to-ridge stations were comparable to those reported for the western mountains (8 to 10°C, vs. 7 to 9°C, Barry, 1992). However, as opposed to their reports, we observed minimum temperature lapse rates that were significantly lower than maximum temperature lapse rates for all the methods and months used.

The frequency distribution and mean maximum and minimum temperature lapse rates varied considerably depending on the base station used, both for daily minimum and daily maximum temperatures. Minimum temperature lapse rates were often inverted (52% of days) when using the valley station (CS01) as the base. A smaller, though still substantial portion of the minimum temperature lapse rates were inverted (35%) when using the sideslope stations as a base. Thus, it appears that cold air frequently pools in the valley floor in the Coweeta Basin, and reaches to at least 150 m above. Predictions based on lapse rates calculated from these stations may in turn be biased. Taken together, these results suggest significant, consistent effects of terrain position on minimum and mean temperatures at valley bottom and adjacent sideslope locations. The use of valley bottom stations or even sideslope stations more than 150 m above the local valley floor for paired lapse rate calculations may lead to significant errors, particularly when predicting minimum temperatures at higher elevations.

Because lapse rates are not constant and depend strongly on terrain position, models which assume constant or long-term average lapse rates should be used with caution. Some models (e.g., MT-CLIM and derivatives, Running et al., 1987; Schaub et al., 1995) use temperature measured at a single base station with historic average lapse rates. Because lapse rates vary temporally, by the terrain position of the base station, and differ for maximum and minimum temperatures, assumptions to the contrary should not be accepted until they have been demonstrated to perform adequately for the biological model of interest.

3.3. Regional temperature prediction methods

Regional regression models had the smallest and least variable errors when predicting daily maxima and minima for the regional data set, however there were no significant differences in the bias for daily maximum or minimum temperatures when comparing the three regional temperature prediction methods (Table 3). Mean absolute errors for both the maximum and minimum temperatures were significantly smaller (p=0.05) when predicted by regional regression than those predicted by the kriging and regional lapse rate methods (Table 3). Larger errors in the regional lapse rate models may have been due to the poor selection of the 'base' station from which to drive lapse calculations. Our test simply selected the nearest station as the base, and applied the estimated regional average lapse rate for the day. Maximum and minimum temperature MAEs were larger for the regional lapse method when compared to kriging and regional regression techniques. We note that these results are based on the estimates of daily extremes for 10 days selected randomly from the 10 years for which the regional data were available. Three days were in winter, four in spring, three during the summer, and two during the fall. Approximately 35 kriging models were fit for each day (34 on some days due to missing data), one for each station, for a total of 338 models. This relatively small number of days was used because of the time required to manually fit semi-variograms and estimate kriging parameters. A common variogram model could not be used throughout, because the best variogram model form differed by day and/or station, and we know of no selection criteria and fitting method which can be easily optimized and automated.

Regional regression models were significant in more than 99% of the days tested, both for the subset of 10 days used in comparing methods, and for the complete 10-year regional data set (1986–1995). First-degree models were most commonly appropriate (78% of the regional regression models fit, with the

Table 3
Comparison of the temperature prediction methods, regional data set. Bias is predicted temperature minus observed temperature, mean absolute error (MAE) is mean after all errors made positive, and standard deviation of signed errors. Models were fit for each of the 10 randomly selected days in the period 1986–1995, successively withholding each of the 35 stations. Error statistics are based on approximately 342 error observations

Temperature prediction method	Bias (°C)	Mean absolute error (°C)	Standard deviation (°C)
Maximum temperature			
Regional lapse model	0.21	2.30	3.23
Regional regression	0.00	1.39	1.77
Kriging	−0.17	1.93	2.64
Minimum temperature			
Regional lapse model	0.07	2.24	3.09
Regional regression	0.00	1.39	1.80
Kriging	−0.05	1.61	2.12

remaining models most commonly exhibiting only one significant 2nd-degree parameter ($p<0.05$). Elevation parameters were significant ($p<0.05$) in more than 90% of the regressions, latitude parameters significant in more than 65% of the regional regressions, and longitude parameters significant in more than 30% of the regression models. Parameters indicated a drop in temperature with increasing elevation or latitude, but a substantial portion of the horizontal coefficients showed increases in temperature with increasing latitude. These positive latitude coefficients may be due to the complex temperature patterns that occur with the passage of frontal boundaries (Barry and Chorley, 1992). Model coefficients had frequency distributions which were right-skew for elevation and symmetric to slightly right-skew for latitude and longitude, however none of these distributions were significantly different from normal (Komolgorov–Smirnov goodness-of-fit test, $p=0.05$). All the three parameters exhibited annual patterns, with temperature coefficients showing the steepest vertical temperature declines and smallest northward temperature declines during summer. We note that the maximum temperature vertical lapse rates were quite similar to those reported by Régnière and Bolstad (1994) in similar models for a somewhat larger region extending further eastward into the Piedmont region. However minimum temperature elevation coefficients in this study showed a significantly smaller elevation effect, here averaging about 5°C/km across all months, while in Régnière and Bolstad (1994) minimum temperature vertical lapse rates averaged near 7.5°C/km. We attribute the difference to more ridge-valley influence in the present data set, with stronger air drainage effects and hence lower temperature decreases with increasing elevation. In all cases, coefficients had larger variances in winter than in summer, similar to the results of Régnière and Bolstad (1994).

Daily elevation coefficients from the regional regressions were serially correlated, based on ARIMA time-series models. These models estimated the serial correlation in the regional horizontal and vertical changes in temperature represented by the regional regression parameters β_0 through β_6, Eq. (3). Previous analyses (Régnière and Bolstad, 1994) have established significant correlation between the daily maximum and minimum temperature deviations from long-term daily normals, and significant autocorrelation in daily temperature series for both maximum and minimum temperature. Results herein indicate there is additional temporal autocorrelation in deviations in regional temperature structure, at least as measured by autocorrelation in daily-fit regional regression parameters. Partial autocorrelations parameters for 25-year daily maxima and minima elevation parameters (β_6) and latitude (β_3) were significant for one-day lags, using Duncan–Watson tests ($p=0.05$). Partial autocorrelations for two-day lags were significant for the minimum temperature elevation and maximum temperature latitude coefficients ($p=0.05$).

Analyses of these regional temperature prediction methods indicate that the differences among regional temperature prediction methods are significant, and prediction errors for daily maxima and minima are typically within 1 to 4°C. The regional lapse method performed poorest. Regional regressions are preferred over kriging when a spatially distributed network of stations is available, at least for the region studied here. The regional regression method provides more accurate estimates of the individual daily temperatures at sites scattered across the region. Kriging-based predictions show higher biases, MAE, and RMSE, and suffer from the additional disadvantages of manual selection and fitting of the variogram model, and the difficulty in automating model estimation for daily temperature predictions. The regional lapse models, although easy to automate and objective in application, exhibit even larger errors. We wish to emphasize the distinction between regional lapse rate models, calculated from the regressions using all stations in our data set (Eqs. (1) and (2)), and local lapse prediction methods, which typically use station pairs (Eqs. (6) and (7)). Tests of local lapse models are provided in the following sections.

The statistical distribution and autocorrelation properties of regional regression coefficients indicate that they may be easily incorporated into the regional temperature prediction models, particularly when used for regional forecasting or long-term simulations. Models have been developed which incorporate maximum/minimum temperature covariance and daily autocorrelation into a regional framework (Régnière and Bolstad, 1994; Régnière, 1996), but which use mean daily, monthly, or seasonal vertical or horizontal relationships. However these models assume average lapse rates which vary on a monthly basis. Stochastic deviations are applied to maximum and minimum temperatures at the base station, and projected across the landscape. However there is further unrepresented stochasticity, in that the lapse rates vary from day to day, and are serially correlated. We are currently modifying and testing our models to investigate how this may alter predictions of biological phenomena.

3.4. Basin and canopy station temperature prediction

Regional regression predictions generally showed negative biases (predicted minus observed) and MAE of from 1.5 to 3°C when predicting station temperatures measured within the Coweeta Basin (Table 4). This independent test showed small positive biases in growing season maximum temperatures for the mid- to high-elevation canopy stations. First through fifth-order lag autoregression show no serial correlation in the daily error time series. Regional regression and lapse models were fit for each day, and predictions compared to independent stations. MAE and standard deviations were lower for the canopy data set, which may reflect better prediction during the growing season, but may also be due to the smaller sample size. The largest errors for maximum temperature were observed at CS21, a low elevation, south-facing station (Table 4). This error may be due to a failure to incorporate the local exposure in the regional regression models. Prediction biases were larger for minimum temperatures than corresponding errors for maximum temperature, as were mean absolute errors and standard deviations. Minimum temperature biases were typically negative. Regional regressions were fit from a network of stations which may have over-represented valley locations, and hence yielded negatively biased predictions. Four of the five of the Coweeta test stations do not receive cold air drainage for a majority of the year, and hence were warmer than valley locations at similar elevations and latitudes. Valley station CS01 was an exception, where predicted temperatures were approximately 0.6 degrees higher than that observed.

We investigated a number of variables as predictors of inversion conditions. These include daily and night-time average windspeed, hourly maximum windspeed averaged for both daily and night-time periods, cloudiness, and combinations of these with precipitation data. We were unable to accurately stratify days with

Table 4
Regional regression prediction error observed at Coweeta stations. Errors are based on predicted minus observed temperatures. Observed temperatures were measured in standard weather stations in forest clearings, predicted temperatures come from daily fits of regional, second-degree, polynomial regression models (Eq. (3)).

Station, variable	Bias (°C)	Mean absolute error (°C)	Standard deviation (°C)	*n* (days)
Maximum temperature				
CS01, Valley	−0.62	1.77	2.63	2547
CS17, NE sideslope	−0.81	1.81	2.45	2544
CS21, S sideslope	−1.90	2.50	2.41	2547
CS28, high sideslope	−0.45	1.83	2.39	2515
L2, Low, s.slope	−0.26	1.14	1.72	183
H2, S sideslope	0.25	0.91	1.84	186
L27, high cove	0.87	1.19	1.53	177
H27, high ridge	0.89	1.22	1.66	201
Minimum temperature				
CS01, valley	0.60	2.10	2.84	2547
CS17, NE sideslope	−2.33	2.64	2.30	2544
CS21, S sideslope	−1.89	2.31	2.53	2547
CS28, high sideslope	−2.91	3.02	2.44	2515
L2, valley/S s.slope	−0.57	1.43	2.03	183
H2, S sideslope	−1.50	1.82	2.11	186
L27, high cove	−2.21	2.06	1.99	177
H27, high ridge	−2.72	2.77	1.87	201

Table 5
Regional regression and lapse prediction errors, canopy stations. Predicted minus observed daily extreme temperatures were derived from weather stations established above the forest canopy (observed) and predicted temperatures based on daily second-degree regional regressions (Eq. (3)) and local lapse models (Eqs. (6) and (7))

Temperature variable station	Bias (°C)	MAE (°C)	Bias (°C)	MAE (°C)	n (days)
Maximum temperature					
L2, Valley/S s.slope	−0.26	1.14	0.24	1.06	183
H2, S sideslope	0.25	0.91	0.21	0.94	186
L27, high cove	0.87	1.19	2.12	2.87	177
H27, high ridge	0.89	1.22	2.89	2.91	201
Minimum temperature					
L2, valley/S s.slope	−0.57	1.43	−0.88	1.17	183
H2, S sideslope	−1.50	1.82	−1.41	0.66	186
L27, high cove	−2.21	2.06	−0.27	0.92	177
H27, high ridge	−2.72	2.77	0.76	1.30	201

inverted from non-inverted vertical lapse rates. Stratification might help, e.g., by selecting more appropriate or different sets of stations or models during conditions likely to produce inverted lapse rates.

Prediction errors for the canopy data set indicate small difference between local lapse and regional regression models when predicting daily maximum temperature (Table 5). They also show that the local lapse model performed slightly better when predicting minimum temperature. Bias and mean absolute error for daily maximum temperatures were generally comparable, from 0.20 to 1.41°C, with the exception of the lapse model for the high elevation station H27, with mean bias and mean absolute error above 2.90°C. Minimum temperature prediction errors for the regional regression model were generally larger than the corresponding local lapse model predictions (Table 5).

3.5. Phenologies and cumulative respiration

Predicted and observed canopy phenologies differed significantly (t-test, a=0.10) at four of the five stations (Table 6). Predicted date of budburst and

Table 6
Predicted bud burst and full leaf expansion based on temperatures observed at canopy stations and based on daily temperatures predicted from the regional regression models (Eq. (3))

Station	Julian day of bud burst and full canopy expansion			
	Based on observed temps.	Based on predicted temps.	p-value, t-test obs. vs. predicted	n (years)
	Julian day, bud burst			
CS01, Valley	106	110	n.s.	10
CS17, NE sideslope	102	116	<0.01	10
CS21, S sideslope	99	115	<0.01	10
CS28, high sideslope	109	129	<0.01	10
CS77, high ridge	130	139	<0.10	4
	Julian day, full canopy expansion			
CS01, Valley	129	134	n.s.	10
CS17, NE sideslope	123	142	<0.01	10
CS21, S sideslope	120	140	<0.01	10
CS28, high sideslope	134	155	<0.01	10
CS77, high ridge	157	164	n.s.	4

Table 7
Predicted and observed annual whole-canopy respiration, based on the daily observed and predicted temperatures for five stations in the Coweeta basin. Predicted temperatures were from regional regression models (Eq. (3)) fit daily to the regional climate data. Canopy respiration was predicted from a locally developed temperature-respiration response function

Station	Predicted annual whole canopy respiration (tons C /ha/year)		p, t-test on difference	n (years)
	Based on observed temperatures	Based on predicted temperatures		
CS01, Valley	2.14	2.12	n.s.	10
CS17, NE sideslope	2.25	1.93	<0.05	10
CS21, S sideslope	2.23	1.98	<0.1	10
CS28, high sideslope	1.92	1.64	<0.05	10
CS77, high ridge	1.68	1.38	n.s.	4

complete canopy development were both later when phenologies were based on the observed rather than the predicted temperatures using the regional regression model. This is consistent with previous comparisons (Tables 4 and 5) where predicted temperatures, particularly minima, were lower than the observed station temperatures. Station CS01 shows the smallest differences of four or five days between predicted and observed phenologies, about 3% of the typical growing season. This difference is most likely to be the smallest because the valley bottom station has terrain conditions most like much of our regional network. Inversions and cold air drainage would depress temperatures at these locations relative to more upland locations, leading to a negative bias when predicting temperatures for stations at upland locations. Errors in predicted vs. observed phenologies were as high as 21 days for upland locations, representing almost 15% of the typical five-month growing season.

Predicted cumulative canopy respiration also differed significantly when based on predicted or observed temperatures (Table 7). Annual respiration was lower for all the five stations, and significantly lower for three of the five. As with phenologies, the smallest difference was observed at the valley station CS01, with the largest difference at the south-facing sideslope station, CS21. Differences ranged for approximately 1% to near 15% of the annual total respiration.

4. Synthesis and conclusions

We observed large, consistent differences in temperature related to elevation, terrain position, and exposure within the Coweeta Basin. Maximum daily temperatures decreased with elevation. However, minimum temperatures showed more complex relationships, and daily minima averaged approximately 2°C lower at a valley bottom location than nearby sideslope measurement stations. Maximum temperatures averaged approximately 1.4°C higher on a south-facing slope when compared to an otherwise similar northeast-facing slope, and there were no significant differences between the minimum temperatures measured at these two stations. Average daily temperature range decreased with elevation, from an average of 13°C at 700 m to 6.6°C at 1440 m. Maximum temperature lapse rates varied by method and stations used in their calculation, showed slight seasonal trends, and averaged 4 to 10°C/km. Minimum temperature lapse rates also varied by season and method, and averaged from −3° to 5.7°C. Valley bottom stations should not be used for estimating the lapse rates, as there appears to be significant cold-air drainage effects, resulting in inverted temperatures and positive lapse rates for more than 50% of the days in this study.

We observed significant differences in the accuracy of regional lapse, regional regression, and kriging temperature prediction models. Regional regression models had biases less than 1.4°C, kriging models had biases less than 2.0°C, and regional lapse mean absolute errors less than 2.4°C. Predicted minus observed biases were larger when we compared the regional regression approach against an independent data set, with averages ranging from 0.2 to 2.9°C. Local lapse models performed approximately as well as regional regression models in comparisons based on a network of stations in the Coweeta Basin. Based on these results, the regional regression and local lapse models are best. Based on these observations, we conclude the regional regression model is the best for predicting the daily maximum and minimum temperatures at landscape scales. It is the most accurate and precise of those tested, and models are simple and easily fit. The local lapse model yielded similar errors in a small test. Although we did not test the geographic limits of local lapse models, we recommend local lapse rate models should not be applied much beyond the proximity of the local stations until further investigated.

Temperature prediction errors using the 'best' performing landscape model, regional regression, propagated through other models. We observed differences that were both biologically and statistically significant when modeling phenology and canopy respiration. Predictions were best in the valley bottom locations, and errors substantially larger in upland locations. Many models are under development and application by which the temperature-dependent processes are driven by spatially-explicit temperature predictions (Aber et al., 1995; Running and Hunt, 1991). Photosynthesis, leaf, stem, and soil respiration, vapor pressure deficit, stomatal conductance, phenologies, and many other biological phenomena are predicted at landscape and larger scales. These predictions presuppose accurate, spatially dense temperature predictions, often at daily and finer time steps. This study identifies a generally applicable method, regional regression, and characterizes the errors in predicted daily maximum and minimum temperatures.

In all, we conclude there is significant landscape variation in temperature in the southern Appalachian mountains which is only partially represented by lapse, regional regression, or kriging models. Our results indicate regional regression models are the most appropriate of the regional temperature prediction models we tested. However, they also indicate that the local lapse models may provide comparable or smaller temperature prediction errors than daily regional regression or kriging models, at least when suitable base stations are chosen and when predicting over the 1 km vertical and 3 km horizontal distances in our local network of stations. Kriging models performed poorly relative to regional regressions, and were more difficult and time-consuming to apply. None of these tested models incorporate terrain position and terrain shape which are related to the non-linear temperature differences such as ridge-top warming or basin cooling. Our results indicate that temperature varies non-linearly between stations due to the terrain position, and this will contribute to prediction errors in models that assume so. None of these methods incorporate the significant landform effects on temperatures observed here, including both exposure-related increases in the daily maximum temperature and airshed-related depression of daily minima. We are aware of no other studies which compare these three commonly applied or proposed landscape temperature predictions methods (lapse rates, regional regression, and kriging), particularly against a large number of independently measured field data. Our results are significant not only in the southern Applachians, in that the mean absolute errors in landscape temperature predictions in other regions may be quite large and depend on the method chosen. Quantitative models of terrain affects on temperature are needed when predicting temperatures in mountainous terrain, particularly cold air-drainage effects on minima and exposure-related increases in daily maxima.

References

Aber, J.D., Melillo, J.M., 1991. Terrestrial Ecosystems. Saunders College Publishing, Philadelphia, PA, p. 429.

Aber, J., Federer, C., 1992. A generalized, lumped-parameter model of photosynthesis, evapotranspiration and net primary production in temperate and boreal forest ecosystems. Oecologia 92, 463–474.

Aber, J.D., Ollinger, S.V., Federer, C.A., Reich, P.B., Goulden, M., Kicklighter, D.W., Melillo, J.M., Lathrop, R.G., Ellis, J.M., 1995. Predicting the effects of climate change on water yield and forest production in the northeastern United States. Climate Res. 5, 207–222.

Barry, R.G., 1992. Mountain Weather and Climate, 2nd ed., Routledge, London. p. 402.

Barry, R.G., Chorley, R.J., 1992. Atmosphere, Weather, and Climate, 6th ed, Routledge, London. p. 392.

Bergen, J.D., 1969. Cold air drainage on a forested mountain slope. J. Appl. Met. 8, 884–895.

Bolstad, P.V., Bentz, B.J., Logan, J.A., 1997. Modelling micro-habitat temperature for dendroctonus ponderosae (coleoptera:scolytidae). Ecol. Model 94, 287–297.

Boyer, D.G., 1984. Estimation of daily temperature means using elevation and latitude in mountainous terrain. Wat. Res. Bull. 20, 583–588.

Cantlon, J.E., 1953. Vegetation and microclimate on north and south slopes of Cushetunk Mountain, New Jersey. Ecol. Monog. 23, 241–270.

Cressie, N., 1985. Fitting variogram models by weighted least squares. Math. Geol. 17, 563–586.
Earth Info. 1993. NCDC Summary of the Day Data. Database Guide, Earth Info, Boulder CO, p. 42.
Hungerford, R.D., Nemani, R.R., Running, S.W., Coughlan, J.C., 1989. MTCLIM: A mountain microclimate simulation model. Res. Pap. INT-414. Intermtn. Res. Stat., USFS, p. 52.
Isaaks, E.H., Srivastava, R.J., 1989. An Introduction to Applied Geostatistics, Oxford University Press, New York, p. 561.
Kaufmann, M.R., 1984. Effects of weather and physiographic conditions on temperature and humidity in subalpine watersheds of the Fraser Experimental Forest, Res. Pap. RM-251, Rock. Mtn. For. and Range Exp. Stat., USFS, p. 9.
Kramer, P.J., 1983. Water Relations of Plants. Academic Press, San Diego, CA, p. 489.
Larcher, W., 1975. Physiological Plant Ecology, Springer, Berlin, Germany, p. 252.
Lauscher, F., 1966. Die Tagesschwankung der Lufttemperatur auf Höhenstationer in allen Erdteilen, Jahresbericht des Sonnblick-Vereines für die Jahre 1962–1964, Vienna, Austria, pp. 3–17.
Lechowicz, M.J., 1984. Why do temperate deciduous trees leaf out at different times? Adaptation and ecology of forest communities. Americ. Natural. 124, 821–842.
Leffler, R.J., 1981. Estimating average temperature on Appalachian Summits. J. Appl. Met. 20, 637–642.
Linacre, E., 1982. The effect of altitude on the daily range of temperature. J. Climatol. 2, 375–382.
McCutchan, M.H., Fox, D.G., 1986. Effects of elevation and aspect on wind, temperature, and humidity. J. Clim. Appl. Met. 25, 1996–2013.
Pannatier, Y., 1993. Exploratory variography and variogram modeling in 2D, in: Capasso, V., Girone, G., Posa, D. (eds.), Statistics of Spatial Processes: Theory and Application, Bari, Italy, pp. 165–170.
Parton, W., Logan, J., 1981. A model for diurnal variations in soil and air temperature. Agric. Met. 23, 205–216.
Pielke, R.A., Mehring, P., 1977. Use of mesoscale climatology in mountainous terrain to improve the spatial representation of mean monthly temperature. Mon. Weath. Rev. 105, 108–112.
Reek, T., Doty, R., Owen, T.W., 1992. A deterministic approach to the validation of historical daily temperature and precipitation data from the cooperative network, Bull. Amer. Met. Soc., 71, 805–809.
Régnière, J., Bolstad, P., 1994. Statistical simulation of daily air temperature patterns in eastern North America to forecast seasonal events in insect pest management. Env. Ent. 23, 1368–1380.
Régnière, J., 1996. A generalized approach to landscape-wide seasonal forecasting in temperature-driven simulation models. Env. Ent. 25, 869–881.
Rosenberg, N.J., Blad, B.L., Verma, S.B., 1983. Microclimate, the Biological Environment, 2nd ed., Wiley, New York.
Running, S., Nemani, R., Hungerford, R., 1987. Extrapolation of synoptic meteorological data in mountainous terrain and its use for simulating forest evapotranspiration and photosynthesis. Can. J. For. Res. 17, 472–483.
Running, S., Hunt, E.L., 1991. Regional hydrologic and carbon balance responses of forests resulting from potential climate change. Climatic Change 19, 349–368.
Russo, J.M., Liebhold, A.M., Kelley, J.G.W., 1993. Mesoscale weather data as input to a gypsy moth (Lepidoptera:Lymantriidae) phenology model. J. Econ. Entomol. 86, 838–844.
SAS Institute, 1988. SAS ETS Manual, SAS Institute, Cary, NC, p. 348.
Schaub, L.P., Ravlin, F.W., Gray, E.R., Logan, J.A., 1995. A landscape framework to predict phenological events for gypsy moth (Lepidoptera:Lymantriidae) management programs. Env. Ent. 24, 10–18.
Schwartz, M.D., 1992. Phenology and Springtime surface-layer change. Month. Weath. Rev. 120, 2570–2578.
Tajchman, S.J., Minton, C.M., 1986. Soil temperature regime in a forested Appalachian watershed. Can. Jrnl. For. Res. 16, 624–629.
Toritani, H., 1990. A local climatological study on the mechanics of nocturnal cooling in plains and basins. Environment. Res. Cent. Pap. 13, Environment. Res. Cent., Univ. of Tsukuba, Ibaraki, Japan, p. 62.
Turner, M.G., Gardner, R.H., 1991. Quantitative Methods in Landscape Ecology, Springer, New York, p. 536.
Vose, J.M., Bolstad, P.V., 1998. Challenges to modeling NPP in diverse eastern deciduous forests: Do we need physiological data at the species level? Ecol. Model., submitted for publication.
Waring, R.H., Schlesinger, W.H., 1985. Forest Ecosystems, Concepts and Management. Academic Press, Orlando, FL, p. 340.
Box, G.E.P., Jenkins, G.M., 1976. Time Series Analysis. Prentice-Hall, New Jersey, p. 575.